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BIMLP Model Based on Deep Learning for Predicting Electrical Load Demand

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Abstract: The accurate prediction of electricity demand is crucial for efficient energy management and grid operation. However, the complexities of demand patterns, weather variability, and socioeconomic factors make it challenging to forecast demand with high accuracy. To address this challenge, this research proposes a novel hybrid machine learning approach for predicting electricity demand. In this research, first, different regression methods were investigated to solve the problem, the results showed that the multi-layer perceptron (MLP) regression model has the best performance in predicting electricity demand. Furthermore, the proposed system, BIMLP (Bagging-Improved MLP), is designed to iteratively improve its parameters using a binary search algorithm and reduce the learning error using bagging, a technique for ensemble learning. The proposed system was applied on the Electric Power Consumption data set and achieved a value of 0.9734 in the r2 criterion. The results of implementing and evaluating the proposed system demonstrate its satisfactory performance compared to existing techniques.

Keywords: MLP, Bagging, Regression, Electrical load demand.

1 Introduction

MAINTENANCE and development of electric power systems is a perpetual activity for all developed and developing societies. To ensure a stable situation, it is essential to have accurate information about the status of generators and distribution substations. Load demand forecasting is a fundamental issue that ensures that the amount of load generated responds to the required consumption and prevents damage to the network [1].

The process of storing electricity is more challenging than storing other energy sources, such as coal and oil. Electricity production, transmission, and consumption occur simultaneously, which can lead to waste if more electricity is produced than needed. Conversely, producing less than required can result in significant economic and social losses. Accurate load forecasting can lead to proper planning and optimal resource management, enabling electricity production and distribution companies to utilize all their resources efficiently [2].

Electricity demand is a measure of the average rate of electricity consumption in a specific area over a certain period [3]. With the increasing modernization of equipment in domestic and industrial settings, electricity demand is also increasing. As this issue is closely linked

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to a country's gross national income and social welfare, it has become a significant concern for policymakers.

Given the dependence of load forecasting on various time factors and geographic location characteristics, traditional models such as time series, econometric methods, and ARIMA models have limitations [4]. The recent popularity of machine learning methods in various domains has created a new opportunity for effective demand management.

Machine learning is a subset of artificial intelligence and computer science that utilizes algorithms inspired by biological behavior to analyze data and make predictions. These algorithms learn from experience, gradually improving their accuracy through experimentation [5]. Recent advances in machine learning have opened up new possibilities for improving the accuracy of electric load demand forecasting. By leveraging these techniques, we can develop more sophisticated models that can capture complex patterns and relationships in the data, leading to more accurate predictions and better decision-making in the electric power industry.

Given the significant financial implications of even small improvements in accuracy, the application of machine learning techniques is highly valued. While existing machine learning-based solutions have shown promise, they often rely on simple models or local datasets, which can lead to inaccurate predictions. In addition, due to the unavailability of data for other researchers, the possibility of comparison for future researches is not provided. In this regard, the aim of this research is to create a more comprehensive and accurate machine learning based solution for predicting electric load demand. To do this, it is first checked which the most effective machine are learning algorithms for predicting electric load demand. Among the various regression methods tested, MLP was selected for further exploration due to its ability to model complex, nonlinear relationships between the input and output variables. Compared to models like Random Forest or Linear Regression, MLP showed superior performance, particularly in capturing intricate patterns in the data. The custom parameters of MLP, such as the number of layers, neurons, and activation functions, were carefully tuned to maximize performance. The ability to adjust these parameters is what gives MLP its flexibility and efficiency in this study. In this way, an attempt has been made to optimize the accuracy of this algorithm by adjusting its parameters and developing it. The proposed approach is tested on a dataset that is accessible to other researchers through the Internet. In the next section of this research, a number of researches that have been recently presented in this field were examined. Next, in the third section, the dataset used in this research will be introduced. In the fourth section, the details of the proposed system of this research are described. The fifth section shows the reviews and evaluation of the results of different parts of the research, and the final conclusion was given in the sixth section.

2 Related Work

In the article [6], a method based on convolutional neural network (CNN) and long short-term memory (LSTM) was proposed for predicting electrical energy consumption in residential houses, which is called CNN-LSTM. This method achieved a performance of 0.37 MSE by examining the effective features in energy consumption. In the study [7], a load forecasting model was presented by combining convolutional neural network (CNN) and bidirectional short-term memory (Bi-LSTM). In this method, two CNNs were used to extract the most important information of the IHEPC dataset. Next, the Bi-LSTM method predicted the load in minutely, hourly, daily and weekly datasets.

In research [8] EA-XGBoost model was proposed, which uses the combination of Empirical Mode Decomposition (EMD), ARIMA model and XGBoost to predict building energy consumption. First, EMD is used to analyze consumption data. After EMD is applied, the results of the ARIMA model are used as an input feature in the XGBoost learning model. The comparison of this method with basic methods showed its proper performance. In research [9] an intelligent hybrid technique based on convolutional neural network (CNN) and bidirectional multilayer long-short term memory (M-BDLSTM) was proposed to predict load consumption. In this research, several CNN layers are used for feature extraction. Next, M-BDLSTM sequential learning method learns the input sequence in forward and backward direction. The implementation results showed that this method achieved the lowest mean squared error with 10-fold cross-validation.

In the study [10], the performance of three different methods including SVR, XGBoost, and LSTM was investigated for building energy prediction. The results of the comparisons showed that the selection of the most suitable method is highly dependent on the natural characteristics of the building energy data, and the adjustment of the algorithms will not have a great effect on their performance. Among the methods examined in this research, the SVR method showed the best performance on the examined data set. In the research [11] three machine learning models including XGBoost random forest and linear regression were used to predict electrical loads and their performance was compared. The results of this research showed that the random forest method has obtained the best results in the regression criteria in the real data set collected from the Tobas region electricity company.

In the study [12], an AI-based approach was presented in which feature extraction was first performed using clustering techniques. To predict energy consumption from DNN model, genetic algorithm was used to determine the optimal architecture of DNN. Evaluation of the proposed method on real data collected from a building in England showed the success of this method. In the article [13], a hybrid method using convolutional neural networks and Echo State Networks was proposed. The method, called CESN, used daily electricity demand data from four sites located in southeast Queensland, Australia, to propose a predictive model. The proposed method was compared with 5 other regression learning methods including SVR, MLP, XGB, DNN and LGBM and obtained the highest performance.

In the study [14], eight single and ensemble machine learning models, including Linear regression, Ridge regression, Lasso regression, Elastic Net, SVR, Gaussian Process, XGBoost and Random Forest, were investigated to predict the energy consumption of healthcare buildings. Among the investigated single methods, SVR method performed best by obtaining 10.67 value in MAPE criterion, while among the ensemble methods, RF and XGBoost obtained values of 9.64 and 9.81 respectively in this criterion. In the article [15], a stacking-based approach called Stacked XGB-LGBM-MLP was presented. In this method, LGBM and XGB techniques are combined at the first level. Predictions made in these methods go to the second level as metadata. In the second level, the MLP technique is used and the final prediction of the system is made by this method on the new data set.

In the paper [16], a method for short-term electric load forecasting is presented, utilizing multi-output Gaussian processes combined with multiple kernel learning to predict 24 load values for the upcoming day. The model is trained on historical data, including load, temperature, and dew point from previous days, with the accuracy of the predictions assessed using the mean absolute percentage error (MAPE).

Paper [11] focuses on forecasting electrical load to ensure a reliable power supply, considering factors like environmental and temporal variables that affect load patterns. Using a real dataset from the Tubas District Electricity Company in Palestine, three machine learning models—Random Forest, XGBoost, and Linear Regression—were evaluated. Among them, the Random Forest model demonstrated the best performance, achieving an R^2 of 87.749%, MAE of 0.03904, and MSE of 0.00270.

Paper [17] proposes an enhanced Deep Neural Network (DNN) model for short-term load forecasting (STLF) in the Jimma town power distribution system, using a Long Short-Term Memory (LSTM) network combined with an Efficient and Parallel Genetic Algorithm (EPGA). The model incorporates various factors such as wind speed, temperature, and load history. The EPGA is used to determine the optimal linear combination of inputs, which is then fed into the LSTM for forecasting. Experimental results show that the EPGA-enhanced LSTM reduces the RMSE by 7.486% compared to the standard LSTM model, demonstrating improved accuracy in load prediction.

In the table 1, a summary of some of the researches carried out in recent years is given. This table provides information about the proposed research method, the type of data examined and the results obtained in each of them.

Table 1 Comparison of previous works.

Research	Method	Data collection	Evaluation
[6]	CNN-LSTM	actual power consumption data from a household in France	MSE/ 0.37
[7]	EECP-CBL	Individual household electric power consumption (IHEPC)	MSE/ 0.049
[8]	EA-XGBoost	Building energy consumption dataset that provided by the US National Energy Laboratory	RMSE/ 47.014
[9]	CNN-M-BDLSTM	Individual household electric power consumption (UCI)	MSE/ 0.3193
[10]	SVR	Data recorded from Chamberlain Halls, University of Birmingham	RMSE/ 2.6210 R2/ 0.9535
[11]	RF	Real dataset of the district energy company (Tubas District Electricity Company in Palestine)	MAE/ 0.03904 MSE/ 0.00270.
[12]	Genetic-DNN	Real office building data in the United Kingdom	R2/0.958 RMSE/ 11.83
[13]	CESN	Data from four sites located in southeast Queensland, Australia	RMSE/32.126 RMSE/34.195 RMSE/17.688 RMSE/3.0503

[14]	RF	Data from general hospital in Shanghai, China	MAPE/ 9.64
[15]	Stacked XGB-LGBM-MLP	ISO-NE	RMSE/ 435.59
[16]	MOGP-MKL	ISO New England database	MAPE up to 4%
[11]	RF	Tubas District Electricity Company in Palestine	MAE of 0.03904
[17]	EPGA-enhanced LSTM	Jimma town power distribution data	RMSE/ 43.87

3 Data Set and Data Preprocessing

In this research, the Electric Power Consumption dataset is used to implement and evaluate the proposed system [18]. This dataset consists of the energy consumption data of the city of Tetouan, which is located in the north of Morocco. This city is located next to the Mediterranean Sea. It has a mild and rainy climate in winter and hot and dry in summer.

The data includes 52,416 observations showing energy consumption in a 10-minute window. 9 features are recorded in each sample of this data set. The characteristics of the samples and the number of samples in this data set are shown in the Table 2.

Table 2. Examples of data in the Electric Power Consumption dataset.

Datetime	1/1/2017 0:00	1/1/2017 0:10	1/1/2017 0:20	1/1/2017 0:30	1/1/2017 0:40
Temperature	6.559	6.414	6.313	6.121	5.921
Humidity	73.8	74.5	74.5	75	75.7
WindSpeed	0.083	0.083	0.08	0.083	0.081
GeneralDiffuseFlows	0.051	0.07	0.062	0.091	0.048
DiffuseFlows	0.119	0.085	0.1	0.096	0.085
PowerConsumption_Zone1	34055.6962	29814.68354	29128.10127	28228.86076	27335.6962
PowerConsumption_Zone2	16128.87538	19375.07599	19006.68693	18361.09422	17872.34043
PowerConsumption_Zone3	20240.96386	20131.08434	19668.43373	18899.27711	18442.40964

In order to use the data set in this research, first the process of pre-processing and feature engineering is done on it. In this process, the characteristics of the hour, day of the week, quarter, month, etc. are extracted from the date time. In addition, 10-day, 15-day and 30-day simple moving averages are extracted from the data set. The final data set used is given in Table 3 and some examples are shown in it.

Table 3. New features in the dataset after feature engineering.

Datetime	1/1/2017 0:00	1/1/2017 0:10	1/1/2017 0:20	1/1/2017 0:30	1/1/2017 0:40
Temperature	6.559	6.414	6.313	6.121	5.921
Humidity	73.8	74.5	74.5	75	75.7
WindSpeed	0.083	0.083	0.08	0.083	0.081
GeneralDiffuseFlows	0.051	0.07	0.062	0.091	0.048
DiffuseFlows	0.119	0.085	0.1	0.096	0.085
PowerConsumption_Zone1	34055.6962	29814.68354	29128.10127	28228.86076	27335.6962
PowerConsumption_Zone2	16128.87538	19375.07599	19006.68693	18361.09422	17872.34043
PowerConsumption_Zone3	20240.96386	20131.08434	19668.43373	18899.27711	18442.40964
Hour	0	0	0	0	0
dayofweek	6	6	6	6	6
Quarter	1	1	1	1	1
Month	1	1	1	1	1

Year	2017	2017	2017	2017	2017
Dayofyear	1	1	1	1	1
dayofmonth	1	1	1	1	1
weekofyear	52	52	52	52	52
SMA10	NaN	NaN	NaN	NaN	NaN
SMA15	NaN	NaN	NaN	NaN	NaN
SMA30D	NaN	NaN	NaN	NaN	NaN

4 Proposed System

Many regression methods can be used to solve the problem of predicting energy consumption. In this research, first, the most important available regression methods were applied to solve this problem in the electric energy consumption dataset. These methods include MLP, Random Forest Regressor, Linear Regression, SVR, Neighbors Regressor, Ridge and XGBRegressor. Among the existing methods, MLP, LinearRegression and Ridge methods had the best performance. The results obtained from these methods are given in the results section. Since the MLP method has many adjustable parameters, this method was chosen to further investigate and improve the results.

The proposed MLP model consists of an input layer, several hidden layers, and an output layer. The network topology is such that the number of hidden layers and the number of neurons in each layer are completely determined through the process of searching for optimal parameters. In this study, a feedforward MLP model is used, in which the hidden layers use the ReLU activation function and the output layer uses a linear activation function to predict the amount of energy consumption. The Adam optimization algorithm with a learning rate of 0.001 and 200 training cycles is used to train the model. To prevent overfitting, an early stopping method is used. Also, the model implementations are done using the Scikit-learn library in Python.

After selecting MLP at this stage, to obtain higher efficiency of this method, the parameters of this model are adjusted based on Successive Halving Search. How to do this is shown in the figure 1. In this section, first things like the total number of allocated resources (R, which is known here as the resource), the number of candidates (n, different combinations of mlp parameters) and the maximum number of algorithm iterations are determined. In fact, each candidate assigns a combination of different values to the mlp parameters. The purpose of this section is to obtain the best candidate that represents the most appropriate parameters for the mlp method.

In the first iteration of the algorithm, each candidate is allocated an equal amount of resources (R/n). Modeling methods are trained on these sources (sample data). Next, each candidate is evaluated. In the next iterations, half of the candidates who are chosen from among the worst will be eliminated. The remaining candidates will receive double the training sample or resource than the previous iteration. This process continues until the last iteration to select the best candidate and provide optimal parameters.

After obtaining the improved MLP (IMLP) model with the help of bagging, the proposed system of this research is strengthened to forecast electric energy demand. The proposed method, referred to as BIMLP, aims to improve the performance and robustness of the IMLP model by leveraging the advantages of Bagging for reducing variance and enhancing accuracy. This method incorporates multiple IMLP models trained on different subsets of the data, which are then combined to produce a more accurate and reliable prediction.

The proposed system of this research is shown in Figure 2. In this bagging-based system, a subset of the original dataset is given to each of the IMLP models. In this method, each IMLP model observes a part of the data set and must build its model based on the same part of the data provided to it (that is, the entire dataset is not given to each IMLP model). For each IMLP model, the data is randomly selected from the training data, so in this selected data, a training sample may be selected several times. In this way, since each model is trained with a different set, it obtains different knowledge. In this way, the output of different models will be different for training and testing data. In this research, the final result is obtained from the arithmetic mean of the results of different methods and the error of the proposed system is reduced.

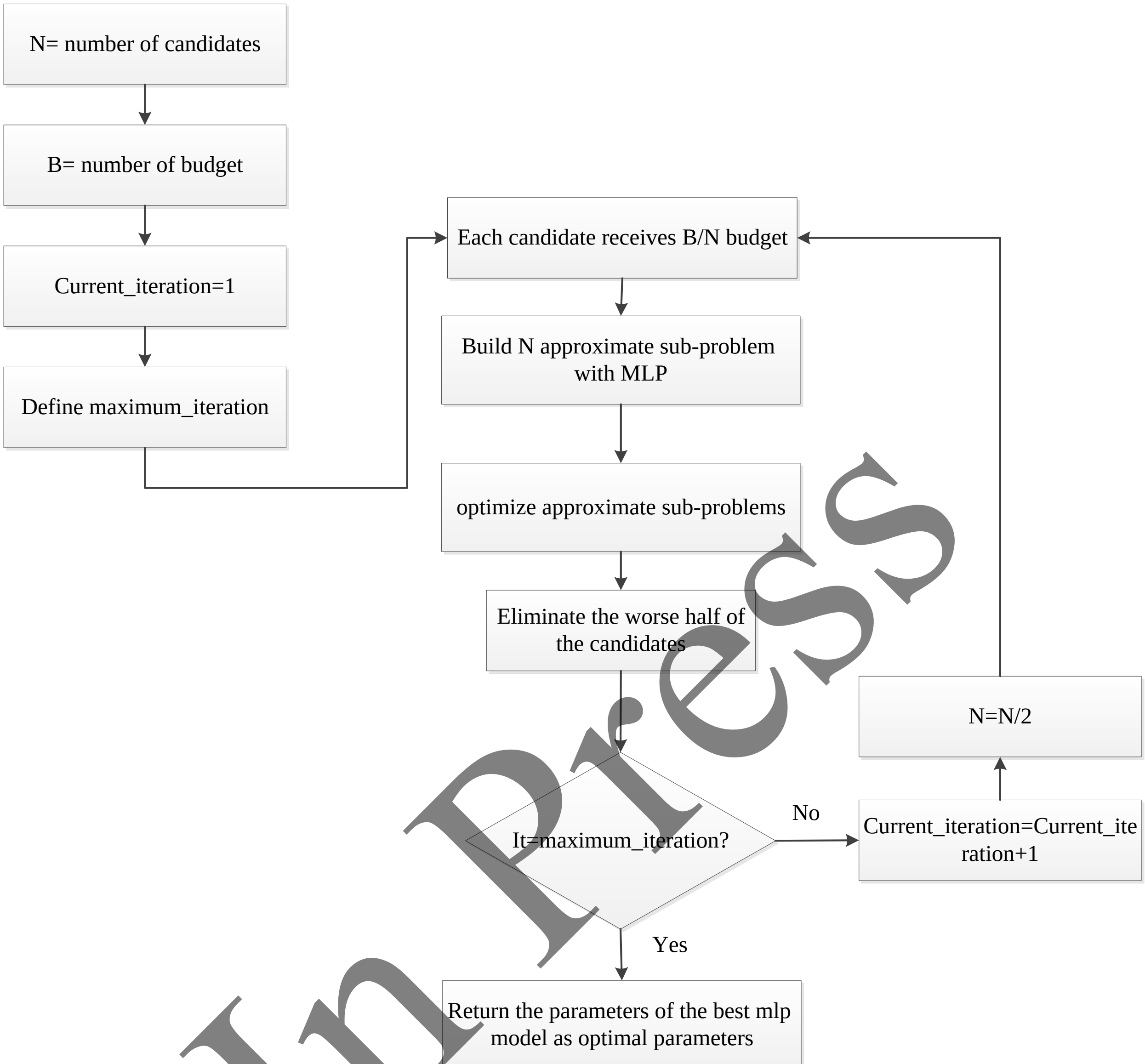

Fig. 1 IMLP with Successive Halving Search.

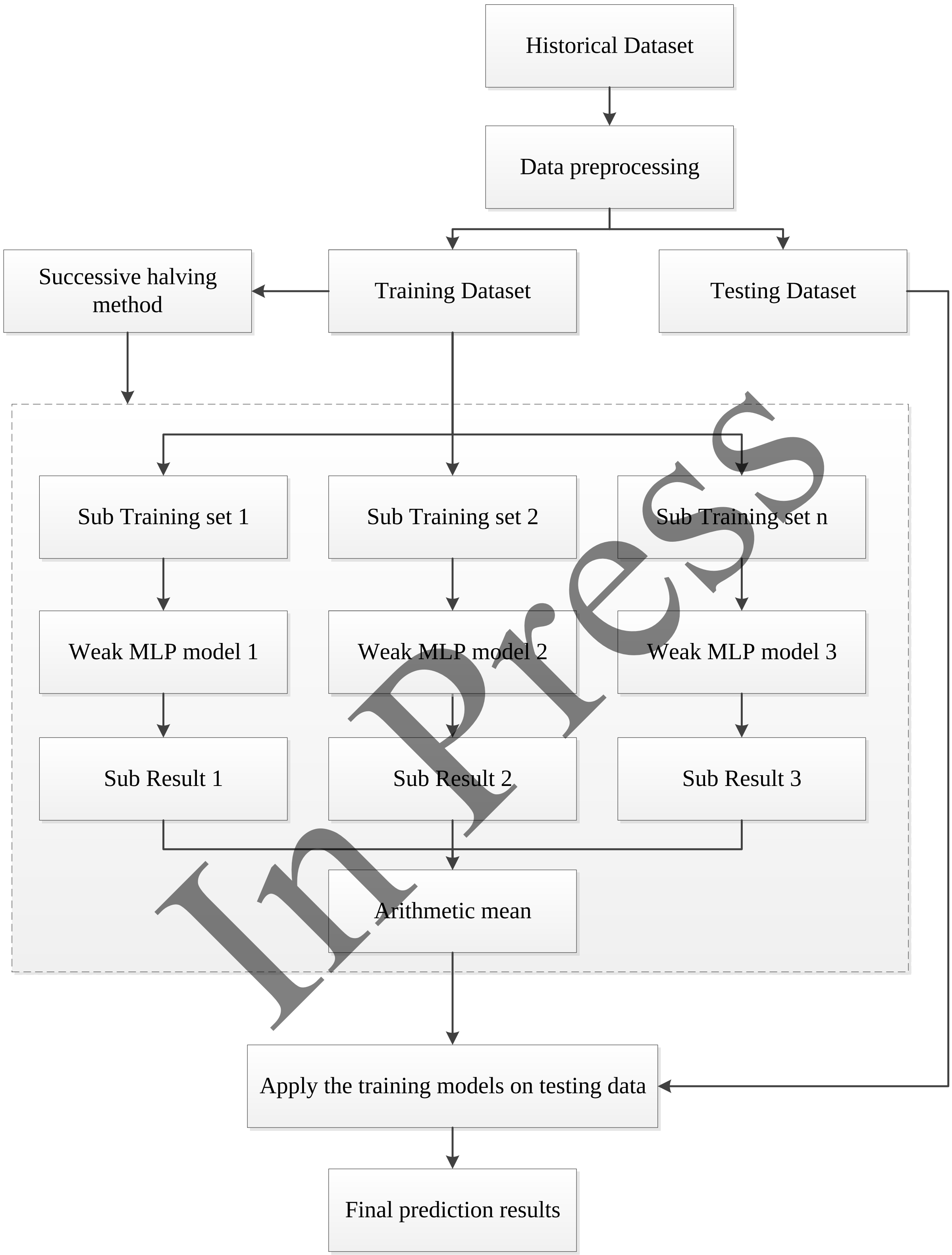

Fig. 2 Flowchart of proposed system (BIMLP).

5 Results

In this section, the results obtained from the investigations carried out in this research are given. In this regard, the results obtained from the regression methods that were examined first are given. In the following, the results obtained from the IMLP methods and BIMLP are given.

These methods are evaluated in terms of explained_variance, MSLE, r2, MAE, MSE, RMSE and MAPE. The explained variance shows the difference between the target variance and the prediction error variance, and the upward trend indicates the improvement of this measure. In logarithmic mean square error (MSLE), first the natural logarithm of each of the predicted cases is calculated and then the mean square error value is calculated. The coefficient of determination (R^2) measure shows how close the regression predictions are to the actual data points. The high accuracy of the model is shown by increasing the value of this criterion.

Mean absolute error (MAE) is measured as the average absolute difference between the predicted values and the actual values. The best value for this criterion is 0 and the worst value is $+\infty$. The mean squared error (MSE) is defined as the average of the square of the difference between the true and estimated values. The behavior of this measure is proportional to the error of each data. The best possible value for it is 0 and the worst value is $+\infty$.

The root mean square error (RMSE) measure shows the average difference between the models predicted values and the actual values. A lower value of RMSE proves the better predictions of the model. The mean absolute percentage error (MAPE) is similar to the mean absolute error, but instead of error, relative error is used. A lower MAPE is also considered as an indication of forecast accuracy.

5.1. Results of regression methods

In the following, the results obtained from the regression methods in the introduced criteria are described. These methods include MLP Regressor, Random Forest Regressor, Linear Regression, SVR, Neighbors Regressor, Ridge and XGBRegressor.

MLPRegressor: The MLPRegressor method is a neural network that can be used to perform regression. This method represents a fully connected multilayer neural network that consists of at least one input layer, one hidden layer and one output layer. The results obtained from applying methods on the data set used in the research are shown in the Table 4. The results obtained in all criteria are acceptable in this method.

Random Forest Regressor**:** Random Forest regressor is an ensemble learning method that is able to perform regression using multiple decision trees in relatively low training time. These trees are applied on different samples in parallel and will be able to cover each other's errors and provide a better result. Based on the results in Table 4, this method has performed weaker than MLP in all criteria except MAPE.

Linear Regression: Linear regression is one of the statistical methods used in the field of data science and machine learning, which has been widely used due to its simplicity and short training time. This method is used to predict the value of a dependent variable based on the value of independent variables. Based on the results in Table 4, this method, like MLP, has provided an acceptable performance, and it has performed weaker in some criteria and stronger in some criteria.

SVR: Support Vector Regression or SVR is a machine learning algorithm used for regression analysis. Unlike other regression models that try to minimize the error between the actual and predicted value, SVR tries to fit the best line to a threshold value. This method has obtained almost the worst result among the investigated methods.

Kneighbors Regressor: KNN regression is a non-parametric method, it approximates the association between independent variables and continuous outcome by averaging the observations in the same neighborhood. This method uses existing data sets to classify and predict new items by finding the most similar items or records already existing. This method has achieved in all criteria compared to MLP and LinearRegression methods.

Ridge: Ridge regression is a method for estimating coefficients of multiple regression models in scenarios where independent variables are highly correlated. This method is applicable in multi-line situations and has acceptable efficiency in the presence of outliers. This method has obtained results very close to the Linear Regression method and is one of the best available methods.

XGBRegressor: The good performance and speed of XGBoost has made this method one of the most popular machine learning algorithms. XGBRegressor is a special regression implementation of XGBoost in Python and is used for regression problems that aim to predict continuous numerical values. XGBRegressor is one of the ensemble algorithms based on decision trees, and due to its regular and parallel processing, it has provided good performance. This method has achieved in all criteria compared to MLP, LinearRegression and Ridge methods.

In the following, the comparison of the results obtained from different regression methods is summarized in the Table 4. By comparing the results of the available methods from this table, it can be seen that MLP, LinearRegression and Ridge methods have obtained better results than other methods in various criteria.

Table 4. Comparison of the results obtained from different regression methods.

Evaluation criteria	MLP	Random Forest Regressor	LinearRegression	SVR	KNNRegressor	Ridge	XGBRegressor
Explained_variance	0.9642	0.8464	0.9662	0.4306	0.9628	0.9662	0.9297
MSLE	0.0016	0.0069	0.0013	0.031	0.0018	0.0013	0.0034
r2	0.9622	0.846	0.9662	0.3827	0.9621	0.9662	0.9228
MAE	866.3546	2086.55	786.2071	4276.7629	907.0922	786.2073	1342.7533
MSE	1649277.6	6714329.5	1473301.4	26915795	1654039.2	1473300.8	3367258.5
RMSE	1284.242	2591.2023	1213.7963	5188.0434	1286.0946	1213.796	1835.0091
MAPE	0.9717	0.9315	0.9752	0.8475	0.9697	0.9752	0.9553

5.2. IMLP results

In this section, the results obtained from the IMLP method are given. For a better comparison of the performance of this method compared to the simple MLP method, the results obtained from these two methods are given in the Table 5. The results of this table show that the IMLP method has improved compared to MLP in terms of explained_variance, MSLE, r2, MAE, MSE, and RMSE, and it has performed slightly weaker than MLP only in the MAPE criterion. This weakness can be ignored compared to the improvements that happened in other measures.

Table 5. The results of applying IMLP on the dataset.

Evaluation criteria	IMLP	MLP
Explained_variance	0.9714	0.9642
MSLE	0.0012	0.0016
r2	0.9708	0.9622
MAE	767.5618	866.3546
MSE	1271157.0821	1649277.5851
RMSE	1127.456	1284.242
MAPE	0.9754	0.9717

5.3. Results of Bagging Regress or on Multiple MLP

In this section, the results obtained from the proposed system method of this research (BIMLP), are given. For a better comparison of the performance of this method and the methods of IMLP and simple MLP, it is given in the Table 6. The results of this table show that the proposed method based on bagging has improved compared to MLP in terms of explained_variance, r2, MAE, MSE, RMSE and MAPE and it has behaved equally with this method in terms of MSLE.

Table 6. The results of applying BaggingRegressor on Multiple MLP on the dataset.

Evaluation criteria	BIMLP	IMLP	MLP
Explained_variance	0.9753	0.9714	0.9642
MSLE	0.0012	0.0012	0.0016
r2	0.9734	0.9708	0.9622
MAE	761.4039	767.5618	866.3546
MSE	1160169.0212	1271157.0821	1649277.5851
RMSE	1077.1114	1127.456	1284.242
MAPE	0.9746	0.9754	0.9717

5.4. Comparison with basic methods

In this section, the proposed system of this research is compared with basic methods. Figure 3 to 9 compare MLP Regressor, Random Forest Regressor, Linear Regression, SVR, Neighbors Regressor, Ridge and XGBRegressor methods with IMLP and BIMLP methods, respectively, in terms of explained variance, MSLE, r2, MAE, MSE, RMSE and MAPE.

As can be seen in these figures, the BIMLP method has performed better than all existing methods in terms of explained_variance, MSLE, r2, MAE, MSE, RMSE.

Although statistical tests were not conducted in this study due to the complexity of time-series data and feature characteristics, we evaluated the proposed BIMLP model against several benchmark models using established performance metrics. The results clearly demonstrated the superior performance of the proposed model across all metrics. These widely accepted evaluation methods are sufficient for assessing model performance, and similar research in the field often employs the same approach.

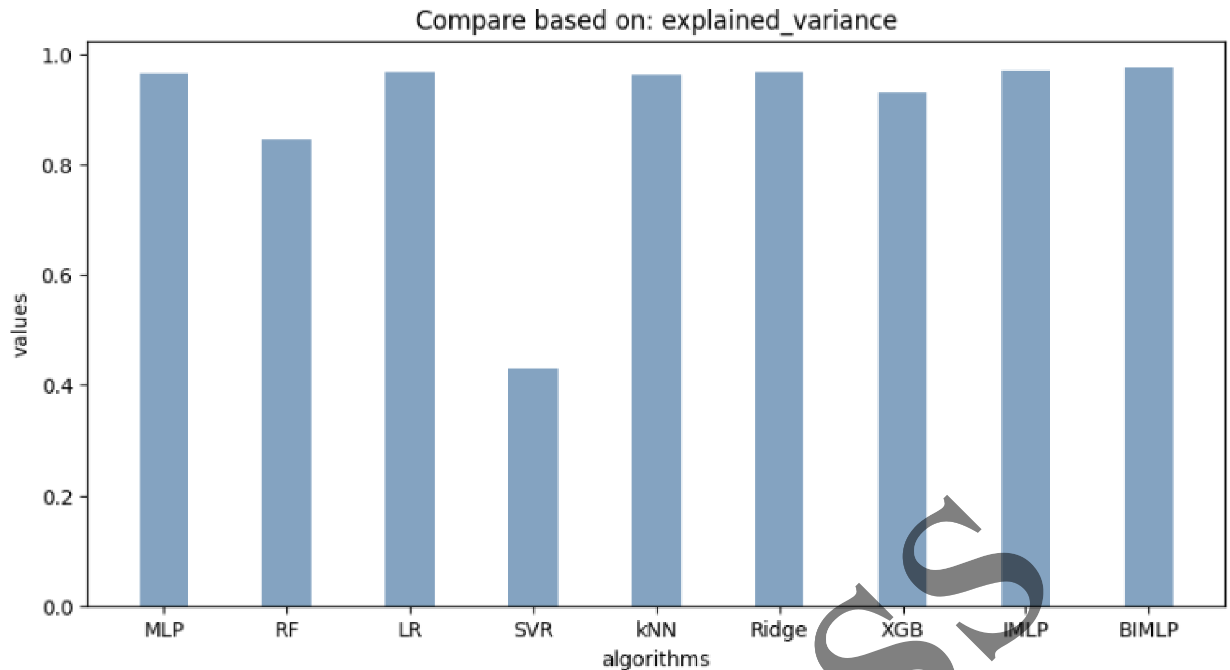

Fig. 3 Comparison of basic regression methods, IMLP and BIMLP in explained_variance criteria.

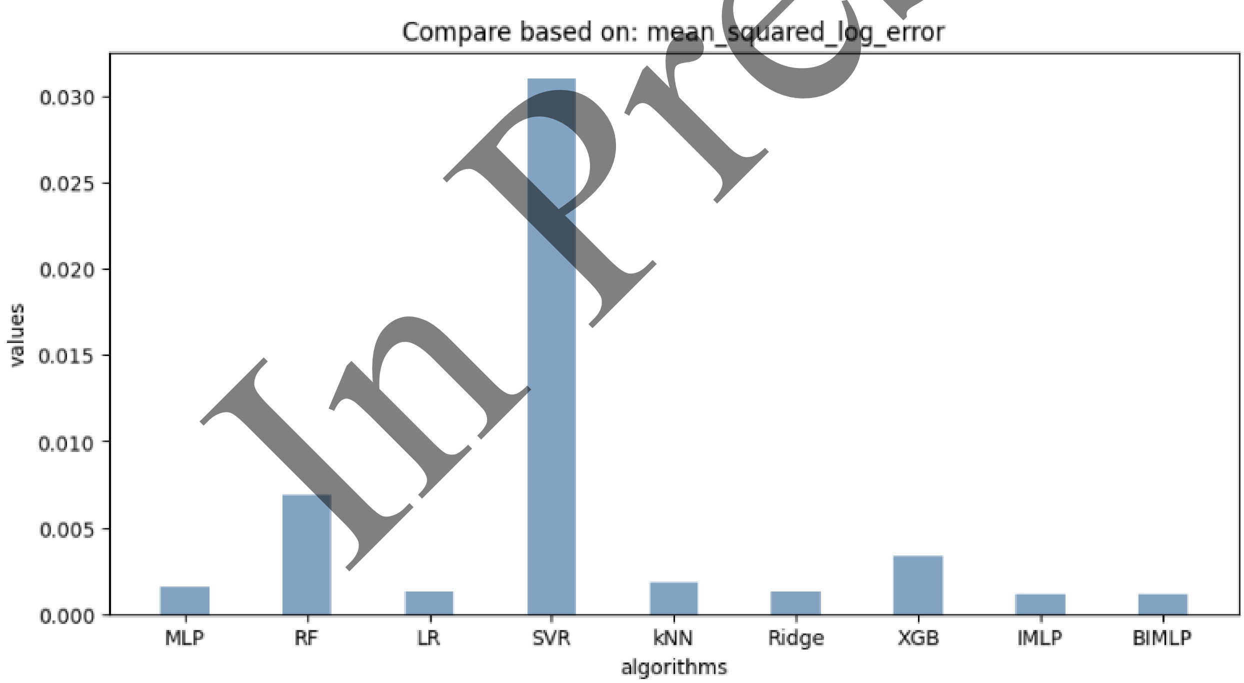

Fig. 4 Comparison of basic regression methods, IMLP and BIMLP in MSLE criteria.

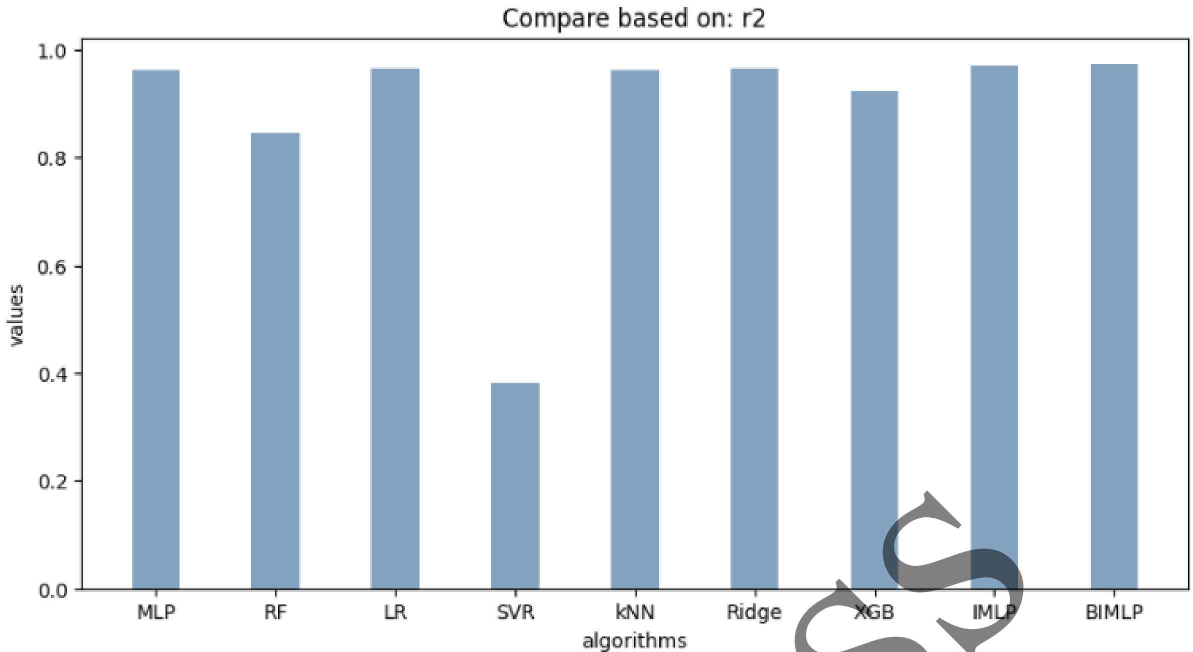

Fig. 5 Comparison of basic regression methods, IMLP and BIMLP in R2 criteria.

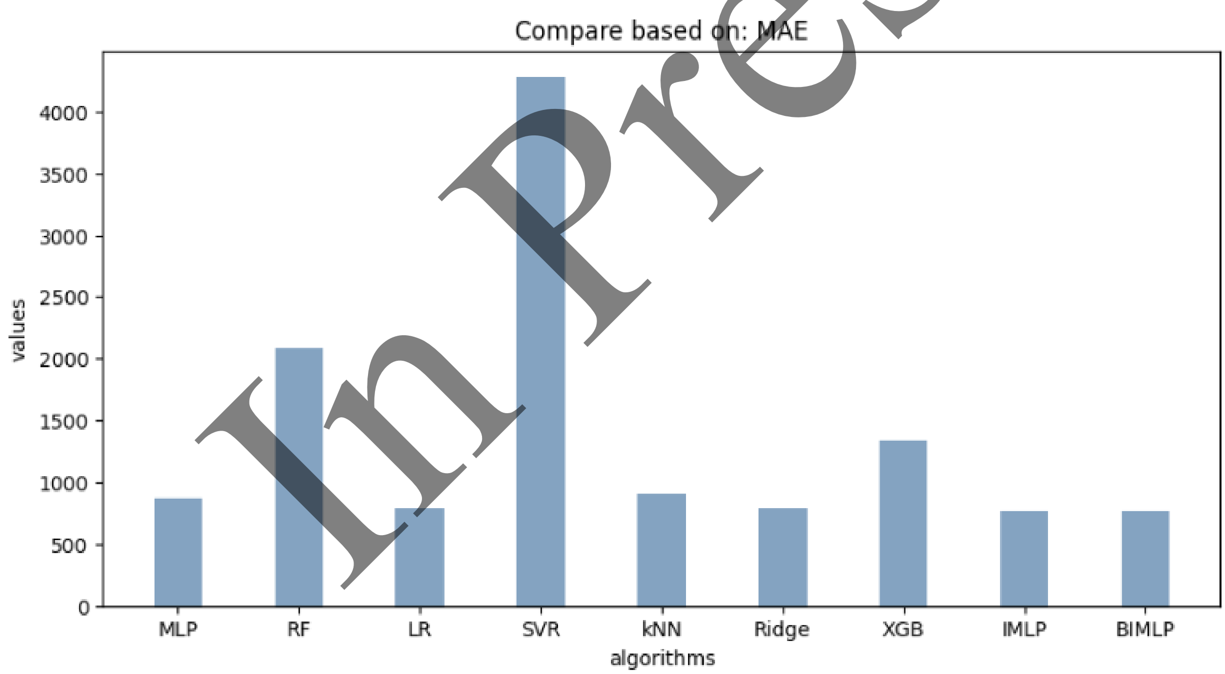

Fig. 6 Comparison of basic regression methods, IMLP and BIMLP in MAE criteria.

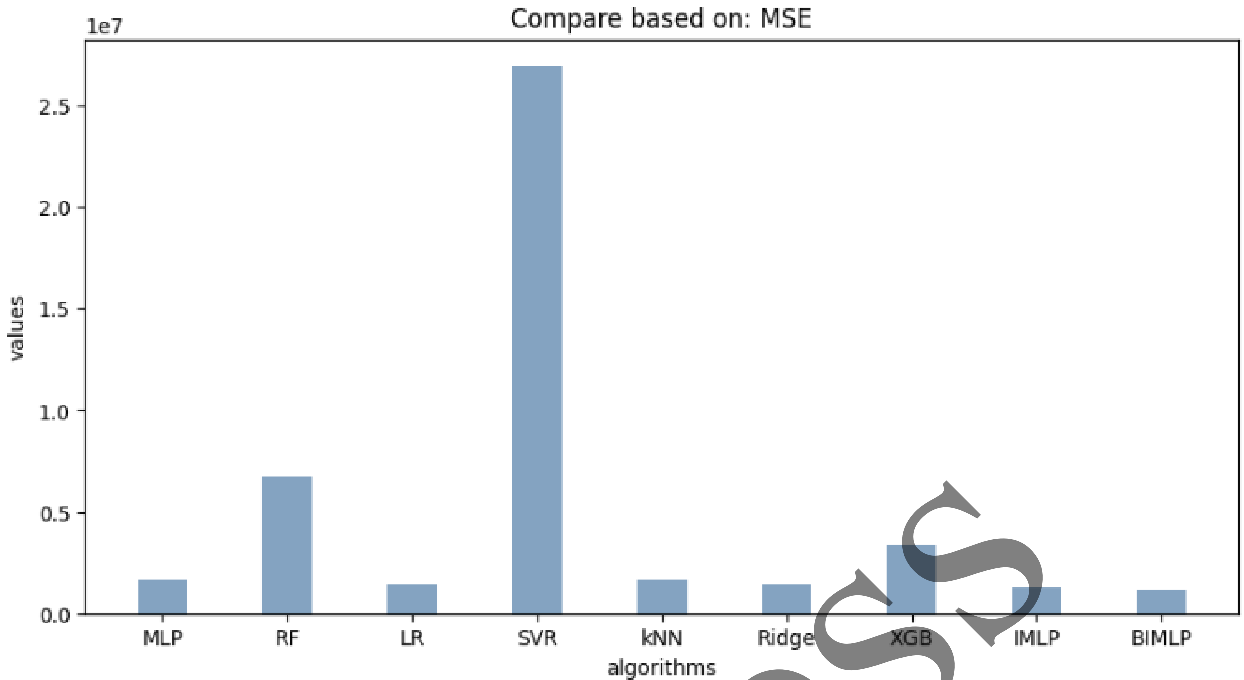

Fig. 7 Comparison of basic regression methods, IMLP and BIMLP in MSE criteria.

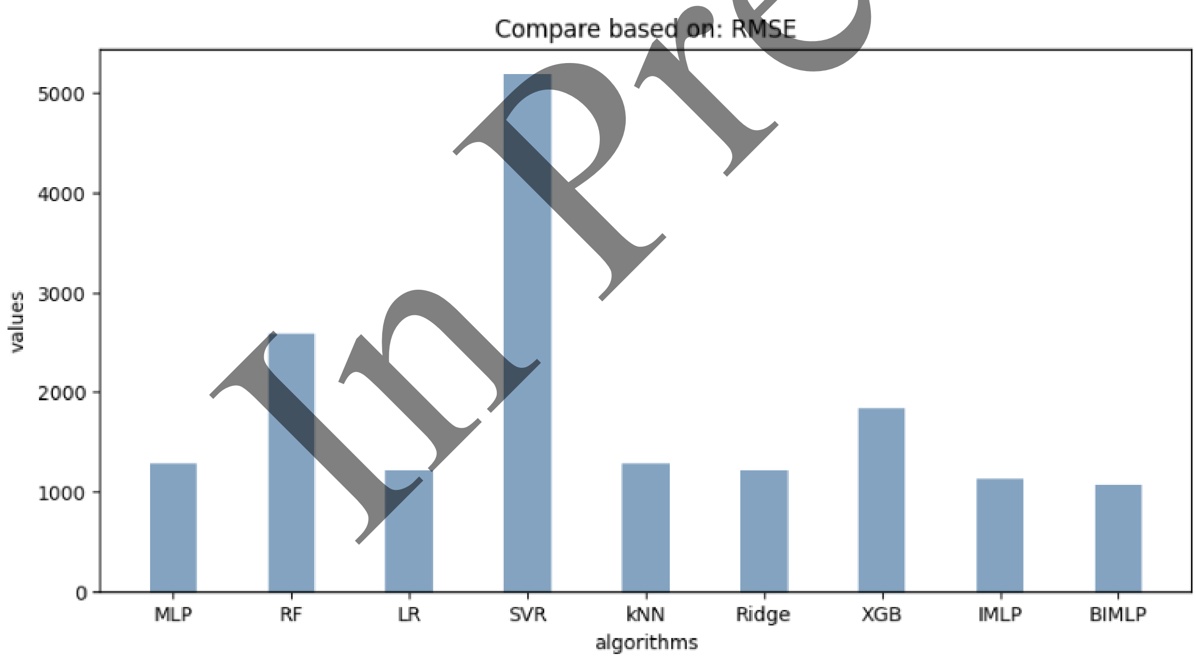

Fig. 8 Comparison of basic regression methods, IMLP and BIMLP in RMSE criteria.

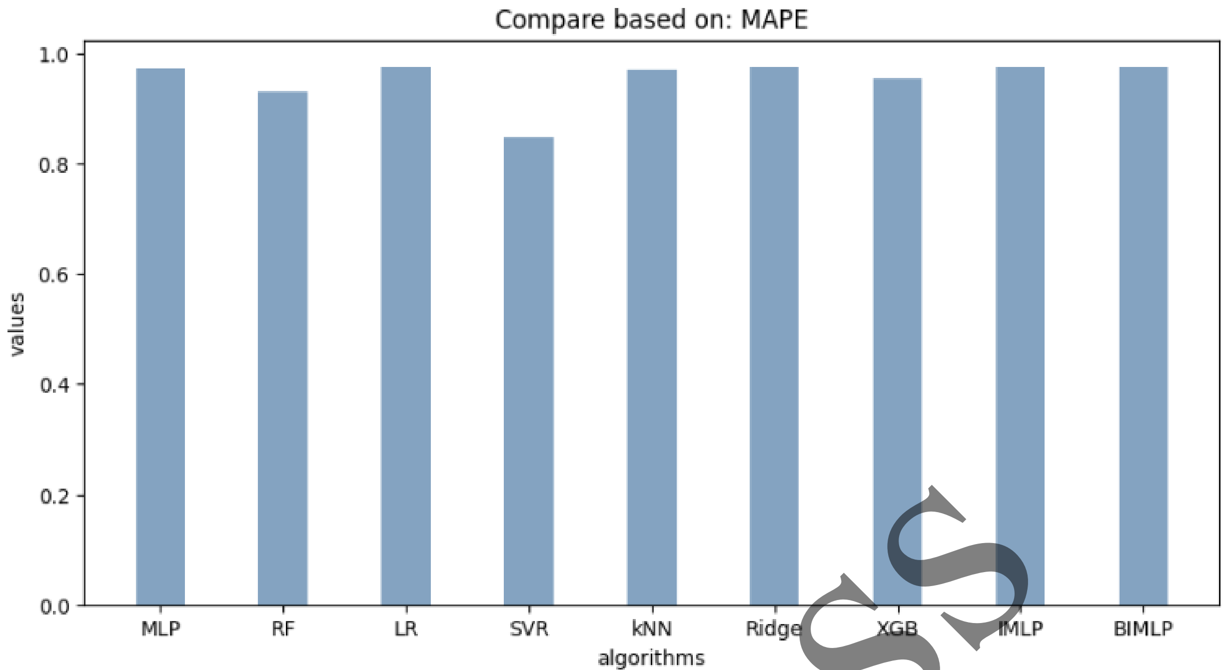

Fig. 9 Comparison of basic regression methods IMLP and BIMLP in MAPE criteria.

5.5. Comparing October and December predictions

In this section, the proposed system of this research is evaluated for forecasting electric energy demand. In this regard, the actual values of energy consumption and the values predicted by the BIMLP model in October and December are shown in Figure 10 and 11 respectively. In these figures, the actual values are shown with red continuous line and the predicted values with green dots. The comparison of these cases confirms the prediction and proper performance of the proposed system of this research.

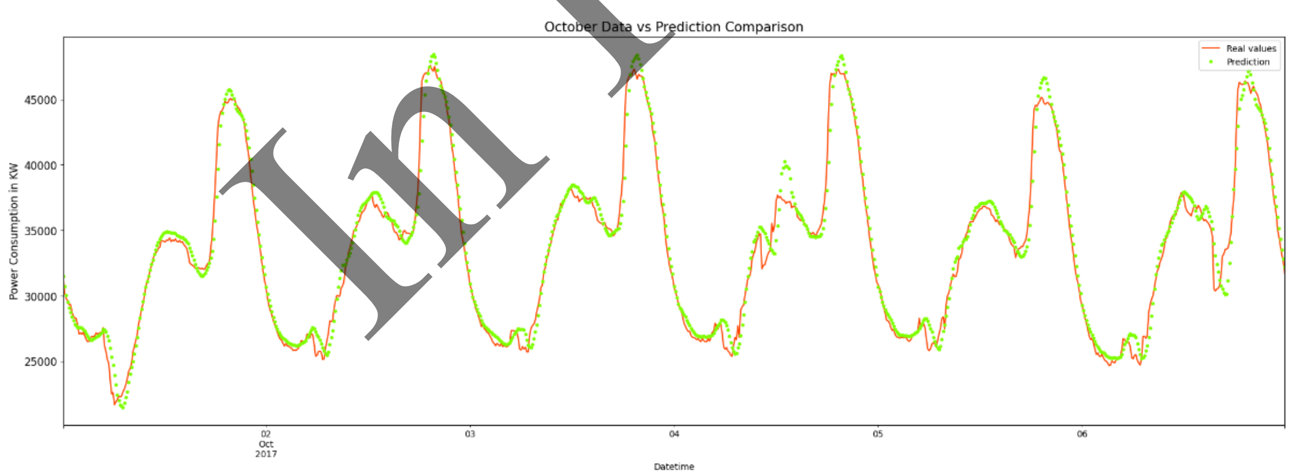

Fig. 10 Comparison of the predictions of the proposed system and the actual values in October.

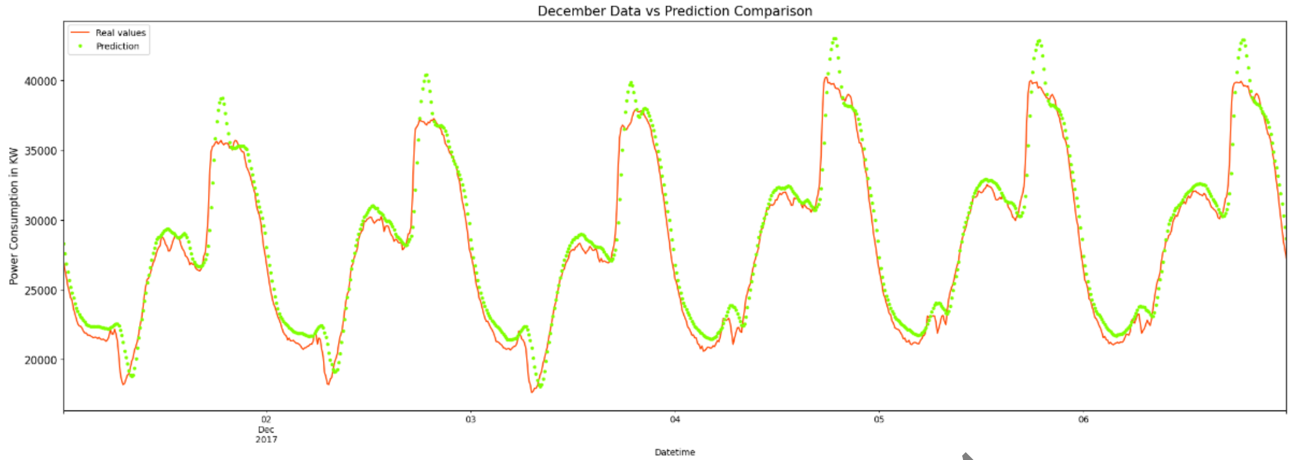

Fig. 11 Comparison of the predictions of the proposed system and the actual values in December.

5.6 Comparison with other methods

In this study, the proposed BIMLP method is compared with two other methods in the research literature [19]. These methods were applied to the dataset of this study. The results show that the BIMLP method performs better than the other methods and the results are recorded in the table 7.

Combined features with a ConvLSTM method provide relatively high accuracy with MAE of 2700.85 and RMSE of 3399.87, but it has lower prediction accuracy than BIMLP. The R^2 of this model is 0.948, which indicates its relatively good performance, but it is slightly lower than BIMLP. Separated features with Parallel ConvLSTM method performs better than the first method with MAE of 1737.32 and RMSE of 2254.91. Its R^2 value is 0.976, which indicates higher prediction accuracy, but it still lags behind BIMLP with R^2 of 0.9734. The proposed BIMLP method with MAE of 761.40 and RMSE of 1077.11 has the best performance among these three methods. Considering the R^2 of 0.9734, this model not only has higher prediction accuracy, but also shows fewer errors compared to other models.

Overall, the results show that the BIMLP method with the least errors and the highest prediction accuracy compared to other methods provides better performance in data analysis. This indicates the high capability of BIMLP in solving the complex problem of electrical load demand.

Table 7. Comparison of the proposed method with the methods presented in [19]

	MAE	RMSE	R2
Combined features with a ConvLSTM	2700.85	3399.87	0.948
Separated features with Parallel ConvLSTM	1737.32	2254.91	0.976
BIMLP	761.4039	1077.1114	0.9734

6 Conclusion

By proposing a solution for electric load demand forecasting, this study contributes to the development of efficient and reliable methods for electricity demand forecasting, which is very important for optimizing energy management and reducing environmental pollution. In this research, firstly, the efficiency of different regression methods to solve the problem of forecasting electric energy demand was investigated. Next, the MLP method was chosen as one of the best methods for strengthening. First, the adjustable parameters of this method were improved using the Successive Halving Search method and the IMLP model was built. This development led to IMLP results. In the following, ensemble bagging method was used, in which a set of IMLP models were used for prediction. In this model, which was called the BIMLP model, each of the IMLP models is given a subset of training data, and finally, the final prediction is calculated from the arithmetic mean of all methods. The results of the investigations showed that the BIMLP method has improved the obtained results in all criteria compared to the MLP method and has obtained the best results compared to the basic methods.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Supervision: Reza Radfar ;Methodology: Somayeh Talebzadeh, Reza Radfar; software: Somayeh Talebzadeh; Validation: Reza Radfar, Abbas Toloie Eshlaghi; Formal analysis: Somayeh Talebzadeh; Investigation: Somayeh Talebzadeh; Writing—original draft preparation: Somayeh Talebzadeh; writing—review and editing: Reza Radfar, Abbas Toloie Eshlaghi;

All authors have read and agreed to the published version of the manuscript.

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Informed Consent Statement

Not applicable.

Appendix

Appendices, if needed, appear before the acknowledgment.

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